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Lifecycle Patterns in the Socioeconomic Gradient of Risk Preferences

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NON-TECHNICAL SUMMARY

While everyone faces risks throughout their life course, individual risk preferences are a highly subjective matter. Some people are fully open to taking risks, while others prefer to avoid them as much as possible. As the circumstances and incentives individuals face change throughout their lives, so too do their risk preferences. In fact, past research has found that risk preferences vary across individuals of different ages, with individuals from older age groups being generally less risk tolerant. Disadvantage concerning education, income, and occupation is another factor which has been shown to influence risk attitudes.

Although there is considerable research on age-group differences in risk preferences, little is known about the ways in which risk tolerance and aversion change as individuals age. This study addresses this gap in knowledge by investigating the degree to which individuals' risk preferences change throughout their life courses, paying particular attention to differences across socioeconomic groups. This is accomplished by using seven waves of nationally representative, panel data from Germany.

Key findings indicate that all individuals experience strong declines in risk tolerance between late adolescence and middle-age, regardless of their socioeconomic position. After middle-age, differences in the effect of aging on risk preference emerge between socioeconomic groups. Specifically, the risk tolerance of individuals with high levels of education or income stabilizes, while that of individuals with low level continues to fall.

These findings suggest that differences exist in the change of risk tolerance over time, and that socioeconomic status partially explains these differences. This is important, as risk perceptions have considerable influences on the decisions that individuals make in a variety of life domains, including their finances, health behaviours, and career choices. As such, a better understanding of the dynamics of risk preferences and the ways in which these preferences change throughout the life course allows policy-makers to better incentivize socially-desirable behaviours.

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Abstract

We investigate which socioeconomic groups are most likely to change their risk preferences over the life course using data from a nationally-representative German survey and methods to separate age from cohort and period effects. Tolerance to risk drops by 0.5 SD across all socioeconomic groups from late adolescence up to age 45. From age 45 socioeconomic gradients emerge - risk tolerance continues to drop for the most disadvantaged and stabilizes for all other groups - and reach a maximum of 0.5 SD by age 65. These results matter because increased levels of risk aversion are associated with imprudent financial decisions in the event of crises.

Keywords: risk preferences; socioeconomic inequalities; life course analysis; cohort effects; SOEP

JEL codes: D81; D01; D63

1 Introduction

Economic theory on risky choices has built over many decades on the assumption that risk preferences are stable both across domains and across time (Stigler and Becker, 1977). Such assumption simplifies the mathematical derivations from economic models, but in practice it is not likely to hold. The circumstances and incentives that individuals face are certainly changing over the life-course. Some studies demonstrate that individual risk preferences systematically vary across birth cohorts due to heterogeneity in the macroeconomic (Malmendier and Nagel, 2011) or institutional (Cameron et al., 2013) climates in which the cohort members grew up, and that macroeconomic shocks may alter risk preferences in adulthood (Guiso et al., 2013). Although many attempts have been made in recent years to understand the age-related differences in risk preferences (Tymula et al., 2013; Mata et al., 2011), almost nothing is known about the individual time-varying properties of risk preferences (see Zeisberger et al., 2012).

In this study we quantify the degree of change in risk preferences as individuals age and explore the heterogeneity in this aging process across the social spectrum. The experimental economics literature, so far, could not fill this gap because it predominantly relies on incentive-compatible measures of risk preferences assembled for college students at one point in time. One exception is Tymula et al. (2013) who collected data on 135 individuals across all age groups, but because of the small sample and cross-sectional nature of the data no conclusions can be drawn about representativeness and true ageing effects. Another exception is Dohmen et al. (forthcoming) who circumvent the problem by using a survey-based, but validated, measure of risk preferences to identify the true ageing-effects of risk preferences over a six-year window. Their study finds that risk tolerance drops monotonically as people age, and the decline is particularly strong for women.

We build on Dohmen et al. (forthcoming), but focus on the heterogeneity in the dynamics of risk preferences over time. Using seven years of the German Socio-Economic Panel (SOEP), we estimate lifecycle patterns of risk tolerance by various definitions of socioeconomic status - education, income, and occupation - to capture all possible channels through which disadvantage can affect risk attitudes. We focus on socioeconomic status because it is one of the most widely used distinctions to describe heterogeneity in attitudes and behaviors and to make policy decisions. To identify the lifecycle patterns in the socioeconomic gradient of risk tolerance we adapt a methodology used in Schurer et al. (2014), van Kippersluis et al. (2009), and Deaton and Paxson (1998) in the context of health and inequality.[1] This methodology allows us to carefully control for the cohort differences by first continuously overlaying the paths of adjusted risk scores of birth cohorts, and then averaging at each age the risk scores over those birth cohorts for which data is available. The sequence of cohort-averaged risk scores over the full age interval, in our case 20-80, approximates the lifecycle pattern of risk tolerance. The aging profile is estimated non-parametrically to allow the possibility that risk tolerance evolves non-linearly over the lifecycle using the same approach as in Schurer et al. (2014) and Kruger and Stone (2008).

This approach - overlapping aging profiles of risk attitudes of birth cohorts - also helps us to solve the identification problem when controlling simultaneously for age, cohort and period effects. It is a widely known result that one cannot separately identify age, cohort, and period effects in linear regression models without additional - often arbitrary - assumptions (see Hall et al., 2007, for an overview). As we estimate age profiles within narrowly-defined birth cohorts, we do not face this identification problem. Theoretically, we could use dummy variables - in our case dummy variables indicating the years running from 2006 to 2012 - to control for the period effects. Instead, we follow in our main specification an approach suggested by Rodgers (1982) and advanced by Heckman and Robb (1985), which controls for the period effect with a proxy variable that captures the underlying environmental factors that cause a period effect in risk preferences. Similar as Dohmen et al. (forthcoming), we assume that the business cycle is one of the most important determinants of risk preferences, and we proxy the business cycle with gross domestic product (GDP) growth rates. The underlying idea is that individuals are more risk averse in economic busts and more risk loving in economic booms (e.g. Brandt and Wang, 2003; Bucciol and Miniaci, 2013). As this is a strong assumption, we also consider time-dummy variables to capture time-specific variations in

[1] All three studies use longitudinal data with eleven (HILDA), eight (ECHP), and nine years (PSID) of length respectively to construct age-profiles by cohort members. For instance, Deaton and Paxson (1998) construct for each birth cohort a dummy variable, and then graph for this birth cohort the health path and the variation in health over the nine years. The individual health paths of all cohorts combined display the lifecycle pattern of health. The same approach is used in Schurer et al. (2014) and van Kippersluis et al. (2009).

risk preferences in a robustness check.

Our measure of risk preference is the response to a general question on whether the individual considers him or herself to be fully prepared to take or avoid risks. This measure is not incentive compatible, and it suffers from the same type of scaling-bias as all measures of self-assessed health, personality, and attitudes. We rely on the work of Dohmen et al. (2011) who validated this measure by comparing its correlation with, and predictive validity of, a standard measure of risk preferences elicited through paid experiments. This measure is used in Dohmen et al. (2012) to explore the intergenerational transmission of risk and trust preferences and in Dohmen et al. (2010) to study the link between cognitive ability and risk preferences.

We find that risk tolerance declines strongly for all socioeconomic groups alike from late adolescence into middle age. From middle age onward, a dramatic gradient in risk tolerance emerges between people at the bottom and the top of the income and education ladder. People living life at the top stabilize, and even increase, their risk tolerance from age 45 onward, while people at the bottom continue to drop at the same rate as observed before middle age. These heterogeneous dynamics lead to a gap in risk tolerance between the two groups of 0.5 standard deviation, which is associated with a 2 standard-deviation difference in cognitive skills. These differences hold across different assumptions made about the period effect, they are not driven by a possible misclassification into socioeconomic class, and they are not explained by systematic panel attrition.

2 Literature Review

Life is full of risks for everyone, yet, preferences over risk is a very subjective matter. Standard economic theory assumes risk preferences to be exogenous and stable (Stigler and Becker, 1977), where stability can refer to both individual variation across situations and across time (See Zeisberger et al., 2012, for an overview of the concepts). Surprisingly, very little is known about the individual-specific nature of change in risk tolerance and aversion over time.

This is not to say that nothing is known about the differences in risk preferences across age groups. Studies based on large samples generally find a negative relationship between risk attitudes and age (see Table A.1 in the Online Appendix for a summary).

For example, Donkers et al. (2001), using data on a set of hypothetical lottery questions administered to individuals aged 16 and above from the CentER Savings Survey (CSS), show that older subjects are significantly more risk averse than younger ones. Dohmen et al. (2011), using both survey-based and experimentally-elicited measures, find a negative relationship between age and willingness to take risks. Bonsang and Dohmen (2012) demonstrate a negative relationship between self-assessed willingness to take financial risks and age in a sample of older individuals aged 50 to 90 across 11 countries using data from the Survey of Health, Ageing, and Retirement in Europe (SHARE).

The behavioral sciences send more mixed signals about the likely age pattern in risk preferences (See Mata et al., 2011, for an overview). Statistics on risk-taking behavior suggest that adolescents/young adults are more likely to take risks than both children and adults, especially so when acting among their peers. One explanation for this heightened level of risk taking in adolescence is not a lack of logical-reasoning ability but a lack of psychosocial maturity (See Steinberg, 2004, 2007).

A meta-analysis of 29 studies assembling data on more than 4,000 observations finds that the pattern of age differences varies as a function of the task and whether the involved tasks involve a learning component (Mata et al., 2011). On average, aggregating all studies that involve a learning component, older adults are more risk-seeking if no explicit information is given in the experiment about the risk probabilities in the gamble. Significant heterogeneity though is found across the task characteristics, which Mata et al. (2011) attribute to differences in the pay-off structures of these tasks. Older adults tend to be more risk seeking in games involving card gambling or financial investment strategies (Iowa Gambling Task, Behavioral Investment Allocation Strategy), and are more risk averse in a task that involves risk taking through a physical exercise (Balloon Analogue Risk Task). On the other hand, aggregating across all studies with tasks that provided full information about the probabilities and outcomes no distinct age-gradients emerge.

Tymula et al. (2013) extend the previous literature by evaluating the age-gradient in risk preferences in both gains and loss domains. This study uses data on 135 healthy urban subjects and behavioral measures of risk derived from decisions concerning monetary rewards in a lottery experiment. The sample includes individuals aged between 12 and 90, which are combined into four different age groups (ages 12-17, 21-25, 30-50, and 65-

90). Importantly, the authors find that older adults are always further away from risk neutrality in both gain and loss domains than any other group: They tend to be more risk seeking in the loss domain, and more risk averse in the gain domain. The oldest age-group members also tend to be most inconsistent in their strategies, which makes them loose the largest amount of income in the experiments relative to all other group members. Further, the authors explain the heightened risk behavior among adolescents that is also reported in Steinberg (e.g. 2004, 2007) with a greater tolerance to ambiguity rather than to risk.

None of the above summarized studies is able to separate out true ageing from cohort effects, even though cohort effects could be the driving force in explaining the age gradient. Malmendier and Nagel (2011) show that macroeconomic conditions, a summary measure for lifetime experiences, have dramatic effects on both the perceptions of risk and investment strategies. Using data from the Survey of Consumer Finances, this study demonstrates that individuals who experienced low stock market returns throughout their lives report lower willingness to take financial risks, are less likely to participate in the stock market, and are more pessimistic about future returns. Cameron et al. (2013) elicit experimentally risk preferences, among others, from 421 urban subjects from Beijing that were born just before and after China had introduced its One Child Policy. Among many emerging behavioral differences, children raised without siblings became more risk averse than children who had to share their parents' attention across siblings.

To the best of our knowledge, there are currently only three studies which assess the individual-specific variation of risk preferences over time (Dohmen et al., forthcoming; Sahm, 2013; Guiso et al., 2013). Using data on self-assessed risk preferences from two household longitudinal studies on individuals aged between 16 and 80, Dohmen et al. (forthcoming) find strong and robust evidence on a negative effect of age on risk attitudes up until age 65. The effects remain when controlling for individual-specific fixed and calendar time effects. Men are more risk-loving than women - a result that is generally found in the literature (Dohmen et al., 2011; Frederick, 2005; Donkers et al., 2001) - but the difference across the sexes rise sharply from adolescence until age 25 until they stabilize in old age. The strong difference in risk tolerance between men and women is consistent with the hypothesis that reproductive competition drives risk preferences, and that this competition is more intense for young men (Low, 2000).

In contrast, Sahm (2013), using data on 18,625 hypothetical-gamble responses from 12,003 individuals between ages 45 and 70 from the Health and Retirement Survey (HRS), finds only a very modest decline in risk tolerance over a window of ten years. Major life events have little impact on the gamble responses, and time varying shocks explain only a quarter of the variation in risk tolerance. She concludes that risk preferences vary mainly across but not within individuals. One reason why Sahm (2013) cannot find significant age effects may be that her sample is restricted to an older age working population followed up until early retirement, while individual change may still be possible before the age of 45.

Finally, Guiso et al. (2013) study the evolution of risk preferences for a group of Italian bank clients before and after the global financial crisis. Their study demonstrates that risk aversion increased significantly by a factor of 3.5 for the median investor between 2007 - just before the onset of the global financial crises - and 2009. More importantly, their study demonstrates that the global financial crisis led not only to an increase in risk aversion for Italian investors - even for the ones that were less affected financially - but that this increased risk aversion was associated with a higher probability to sell stock holdings during the worst moment of the crisis, leading to higher real losses. These findings emphasize the importance of controlling for period effects, that have been so carefully accounted for in Dohmen et al. (forthcoming).

Some studies interpret the negative age effect as a true ageing effect in terms of cognitive decline. As the ability for attention, memory, learning, and cognitive control declines from about age 20 onward (Baltes and Lindenberger, 1997; McArdle et al., 2002), individuals adopt different strategies to respond to risk. High levels of cognitive functioning have been strongly linked with high levels of risk tolerance (Frederick, 2005; Burks et al., 2009; Dohmen et al., 2010; Benjamin et al., 2013). Using data from SHARE, Bonsang and Dohmen (2012) find that at least 70% of the correlation between risk preferences and age can be attributed to cognitive skills, and this insight holds for a representative sample of older individuals from 11 European countries. Other explanations for an age-gradient in risk aversion are that as people age their motivation declines and emotional regulation abilities improve leading to a reduced willingness to take risks (Mata et al., 2011).

If it is true that an increase in risk aversion over the life course is caused by cognitive decline, then not everyone in the population should alter their risk preferences alike.

Some individuals are more at risk of losing their cognitive abilities, while others age healthily (for similar arguments see Tymula et al., 2013). In fact, heterogeneity in the aging process has been reported widely (See Schurer et al., 2014, for an overview). Most dramatic declines in cognitive functioning are likely to occur within occupations which require little skills or learning over time such as manual, highly-routinized work. Hence, a socioeconomic gradient in risk aversion is likely to emerge as people age physically.

An alternative pathway via which a socioeconomic gradient emerges over the lifecycle is through the increased frequency of negative life events. Generally, risk aversion is more common among individuals with lower levels of education or economic means (Donkers et al., 2001; Dohmen et al., 2011).[2] Disadvantaged families may experience such negative events more often. For instance, manual and low-skilled occupations, a defining characteristic of the working class, tend to experience a larger number of accidents at the workplace and are more exposed to job loss during economic downturn. As life goes on, the frequency of these negative events increases, but it may be disproportionately so among groups at the lower end of the social ladder. As a consequence, through experience individuals from disadvantaged backgrounds should be more likely to develop risk aversion than individuals from privileged backgrounds.

In this study, we are not testing one hypothesis against the other - in fact they may work in conjunction - but we will explore heterogeneity in the dynamics of risk preferences that is consistent with both hypotheses.

3 Data and variable definition

3.1 Data

To carry out the analysis we use seven waves of data from the German Socio-Economic Panel covering the years 2004, 2006, and 2008-2012. The SOEP is a longitudinal survey of private households established in West Germany in 1984, which extended its sample after Germany's reunification to include the new Bundeslaender.[3] In its first year the study

[2] Tymula et al. (2013) cannot find any socioeconomic gradient in experimentally elicited risk preferences.

[3] The data used in this paper was extracted from the SOEP Database provided by the DIW Berlin (http://www.diw.de/soep) using the Add-On package SOEP Info for Stata(R). It uses the 95% Scientific sample obtained from Cornell University.

included 5,921 households from which 12,245 individuals were successfully interviewed ("German West" and "Foreigner" sample). Further samples were added in consecutive years including the "German East" (1990), "Immigrant" (1994/1995) and the "Refreshment" (1998) samples. The SOEP achieved a reasonably high first wave cross-sectional response rate of 64.5% and has an average longitudinal response rate of 92.2% (Wagner et al., 2007). The study is set up as life panel, where the household is sampled as a unit, and the members of the households are traced and interviewed by professional interviewers every year from age 17 onward.

Our estimation sample for the pooled analysis comprises 135,807 person-year observations, or 36,105 individuals observed over nine years (2004-2012). Around 26% of the sample members remained in the sample over the full interval. Another 10% stayed in the sample over the full time period, but missed one year of the interview. The median length of stay in the sample is 5 waves. For the cohort analysis, in which we follow the individuals over time, our sample is restricted to 18,990 individuals or 96,108 person-year observations for whom complete data is observed in 2004. In this sample, 67% are observed in all waves available.

3.2 Variable definitions

3.2.1 Risk preferences

In the years 2004, 2006, and 2008-2012 the SOEP included several questions on risk preferences as part of the standard person questionnaire. We focus on the general risk question which asks the respondent "How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'". The same measure is used in Dohmen et al. (forthcoming), Dohmen et al. (2012) and Dohmen et al. (2010).[4] Larger values on this self-assessed measure indicate greater tolerance of risk. We refer from here on to this measure as risk tolerance.

In our analysis, we assume this measure to be approximately continuous. We also

[4]Non-response is very low. Less than 0.5% of sample members refused to answer the risk preference question.

construct binary measures of high levels of risk tolerance (risk tolerance score of 7 or higher) and extreme levels of risk aversion (risk tolerance score of 0) that will be used in a complementary analysis to better understand the determinants of extreme risk preferences. Roughly 20% and 6% of the sample members are located within the right and left tail of the distribution, respectively (see Table 1).

Although this risk-assessment measure is not incentive compatible, Dohmen et al. (2011) have shown in a validation study that it is a meaningful proxy for a standard risk-preference measure elicited from an incentivized lottery experiment. Dohmen et al. (2011) sampled 450 German individuals from all age groups using the same sampling framework as the SOEP survey. The team administered both a survey and conduced a paid lottery experiment on this nationally-representative sample.[5] The value of the safe option at the switching point, i.e. the value at which individuals become indifferent between the safe option and the lottery, was regressed on self-rated risk preferences controlling for a battery of potentially confounding variables. The estimated coefficient on the self-assessed risk measure ranges between 0.4 and 0.6 and is highly statistically significant despite a small sample of 383-450 individuals. Dohmen et al. (2011) also found that the general risk question is the best all-round indicator for risk attitudes, while each specific risk measure has the most explanatory power in a specific context such as car driving, financial matters, sports and leisure, health, and career.

3.2.2 Socioeconomic status

To measure socioeconomic status (SES), we derive three standard measures from: (1) Disposable household income; (2) Educational attainment; and (3) Occupation status (See Schurer et al. (2014) for the same definitions). All three dimensions are considered because of the various pathways how socioeconomic disadvantage can affect risk preferences (Donkers et al., 2001; Dohmen et al., 2011).

We define four income groups by constructing income quartiles from equivalized household disposable income which adjusts for the needs and the number of members of the

[5]The experiment asked participants to choose from a lottery with equal probability to earn 300 Euro or 0, and 20 rows of safe options starting from 0, 10 to 190. Starting from 0, a participant will switch from the lottery to the safe option at some row. The value of this safe option represents the risk attitude of the participant, and only the extremely risk seeking person will choose to switch at 190. The experiment was incentive compatible and could reveal real risk attitudes as the participants had a 1 in 7 chance to win and the payment will depend on the choice the participant made on the rows.

household. The needs adjustment is based on the modified OECD scale which gives a weight of 1 for the first adult, 0.5 for subsequent adults (aged over 14) and 0.3 for each child (Hagenaars et al., 1994). Income is a good indicator for the immediate access a household has to goods and services, however it does not capture accumulated wealth.

Educational attainment is defined by the highest educational qualification an individual has ever achieved. We generate four categories: minimum schooling or less, apprenticeship certificate, higher vocational degree, and university degree. The educational-attainment measure has the advantage that it is fairly stable in adulthood. Among all three SES measures, education is most likely to tell a story of risk-relevant lifestyles and behaviors, and, due to its fixed attribute, it is reflective of childhood socioeconomic position.

Occupational class is defined as belonging to an occupational group based on the two-digit code of the International Standard Classification of Occupations (ISCO-88). We distinguish eight categories ranked in order of skill intensity: Professional, legislator/manager, technician, service employee, skilled agricultural worker, craft worker, machine operator, and elementary worker. The same classification is used by the International Labour Organization (ILO) to define groups according to the tasks and duties undertaken (United Nations, 2010). As some persons changed their occupation over time, we assign the highest occupation ever attained. In some cases the individual did not have an occupation (e.g. when unemployed in one particular year). For these cases, we assigned the occupation from the last employment observed. Details about occupation reassignment can be found in Tables A.2 and A.3 in the Online Appendix.[6] Occupation is the structural link between education and income: it provides a measure of environmental and working conditions, and cognitive and psychological demands of the job.

Summary statistics of all variables used in the analysis are provided in Table 2.

[6]For 43,965 person-year observations we initially had no occupation code. We are able to reassign an occupation code for 13,815 individuals by backtracking employment histories. For the remaining 22.2% of the estimation sample we find no occupational code. These are mainly older women who never entered the labor market. By re-assigning occupational codes, we face the problem of classification error. This is particularly likely for individuals who changed occupations more than three times. In fact, 38% of the sample have more than one occupational classification, and 4% have more than three occupations through their lives. In a robustness check to the main results, we were able to show that removing individuals with more than 3 occupational codes does not alter our conclusions. Provided upon request.

4 Estimation strategy

We start our analysis by estimating the determinants of risk tolerance. Let RT_{it} be the level of risk tolerance of individual i reported in period t, which is a function of observable characteristics (X_{it}), an individual-specific random effect (ν_i), and random shocks ε_{it}:

$$RT_{it} = X_{it}\beta + \nu_i + \varepsilon_{it} \tag{1}$$

The error terms ε_{it} and ν_i have a distribution of mean zero and constant variance and are assumed to be independent of the regressors X'_{it}. Due to the longitudinal nature of the data, we are able to exploit both the within- and across-group variation, which ensures efficient estimates. Allowing for individual-specific, random variations in self-reported risk attitudes, we are able to control to some degree for heterogeneity in self-reports (For simular arguments, see Schurer et al., 2014, in the context of self-assessed pain).[7] The control vector X'_{it} includes measures of socioeconomic status (SES) such as education, household income, occupational status in addition to labor force status (inactive, unemployed), gender, marital status, foreigner status, children in the household, and health status (high blood pressure, stroke, cardiovascular disease, depression, cancer, and dementia). We also control for period - sometimes referred to as calendar time - effects. This is important because several studies have shown that the outside environment - individual background risk (Guiso and Paiella, 2008) or the perception of catastrophic events (Caballero and Krishnamurthy, 2009) - can strongly alter risk attitudes. Such an important event, the global financial crisis triggered in 2008, falls directly in the middle of our available sample time periods. Guiso et al. (2013) have demonstrated for a sample of Italian investors that risk aversion increased significantly by a factor of 3.5 for the median investor between 2007 - just before the onset of the global financial crises - and 2009.

To document the socioeconomic gradient in risk tolerance by age, we first estimate a linear random effects model and predict the unexplained, permanent part of risk tolerance purged of the influence of all control variables and SES (omitting one category of SES, e.g.

[7]In an additional analysis, we estimate the odds ratios of reporting high levels of risk tolerance (risk tolerance of 7 or higher) and extreme levels of risk aversion (risk tolerance score of 0) using a random effects logit model. This will allow us to explore heterogeneity in the age effect and assess a possible asymmetry of the age effect at the extreme ends of the risk tolerance distribution.

occupation when constructing the risk-attitude age gradient by occupational groups). In a second step, we apply bivariate kernel regression methods to estimate the relationship between the permanent component in risk tolerance and age for the socioeconomic group that was omitted from the list of SES control variables in the first-step regression model. Kernel regression methods are flexible as they do not impose a functional form for the relationship between risk attitude levels and age (Wand and Jones, 1995). The estimated relationships between risk tolerance and age are plotted graphically between the ages of 20 and 80. A similar procedure was used in Kruger and Stone (2008) and Schurer et al. (2014) to plot pain-age profiles. Permanent risk tolerance levels are standardized to mean 0 and standard deviation of 1 in all samples to express differences in risk tolerance across the socioeconomic groups in terms of sample standard deviations.

Although this specification allows us to exploit some features of the longitudinal data, we do not have enough time periods available to truly follow the risk-preference profiles from late adolescence into old age. At maximum, we have nine years of data available - seven actual data points - over which we could follow individuals. Therefore, we cannot judge whether the age effects represent true aging or differences in risk preferences across birth cohorts. To solve this identification problem we overlap aging profiles of risk attitudes of individuals born in the same year so that we can follow individuals from late adolescence into old age. The lifecycle patterns of risk tolerance are therefore approximated by averaging risk tolerance levels across overlapping birth cohorts in each available age-group (See Schurer et al., 2014; van Kippersluis et al., 2009; Deaton and Paxson, 1998, for applications in health). This method involves four steps: in a first step we generate twelve birth cohorts each born within a five-year window; in a second step we estimate the permanent component in risk tolerance as outlined above for each of the twelve birth cohorts; in a third step we estimate non-parametrically for each cohort and each socioeconomic group the relationship between the permanent component in risk tolerance and age; in a fourth step, we average at each age-data point the permanent component in risk tolerance across the overlapping cohorts.

Similar to Schurer et al. (2014), van Kippersluis et al. (2009), and Deaton and Paxson (1998) we define a birth cohort for a five-year interval. The oldest birth cohort includes individuals born between 1930 and 1935 (average age of 72 in 2004 and 80 in 2012) and the youngest birth cohort includes individuals born between 1980 and 1985 (average age of

22 in 2004 and 30 in 2012). Each of the twelve cohorts can be followed over seven years.[8] The overlapping risk tolerance paths of these cohorts are then plotted non-parametrically by socioeconomic groups: (1) minimum education versus university education, (2) low versus high household income, and (3) manual/elementary versus professional/managerial occupations.

Table 3 illustrates the idea with four birth cohorts. The 1940-44 cohort ages from 60 to 72 during the seven waves of the panel; the 1945-49 cohort ages from 55 to 67; the 1959-54 cohort ages from 50 to 62; and the 1955-1959 cohort ages from 45 to 57. For instance, at ages 60, 61, and 62, we have three overlapping cohorts, and at age 59, we have two overlapping cohorts, and so on. In the full data, age effects are identified by three cohorts for age-groups 30 to 65, by two cohorts between 25 and 30 and 65 and 70, and by one cohort for individuals younger than 25 and older than 72. The advantage of our data is that for every birth cohort at every considered age-data point we have 1000-2500 observations (see Table A.4 in the Online Appendix) in the aggregate, and between 42-150 observations for the smallest socioeconomic groups (see Tables A.5 - A.8 in the Online Appendix).

This approach - overlapping aging profiles of risk attitudes of twelve birth cohorts - helps to avoid the identification problem when estimating simultaneously age, cohort and period effects. It is widely known that one cannot separately identify age, cohort, and period effects in linear regression models without additional - often arbitrary - assumptions (see Hall et al., 2007, for an overview).[9] As we estimate age profiles within each birth cohort, we do not face this identification problem. Theoretically, we could use dummy variables - in our case dummy variables indicating the years running from 2006 to 2012 - to control for the period effects. Instead, we follow an approach suggested by Rodgers (1982) and advanced by Heckman and Robb (1985), which controls for the period effect with a proxy variable that captures the underlying environmental factors that cause a period effect in risk preferences.

[8]Strictly speaking, we follow each birth cohort over a time interval of nine years, i.e. from 2004 to 2012. However, we have only in seven of the nine years data available on risk preferences. This leaves us with two gaps in the data sequence, for which the change in age is two years instead of one, a trade-off we have to make to maximize the total number of time observations available for each individual.

[9]For instance, Mason et al. (1973) proposed that the effects can be estimated if the coefficients of some of the dummy variables are restricted. This approach requires a priori knowledge of which effects are most likely to be the same, e.g. the effect of the youngest and the oldest age cohorts, and assumes additive separability. This approach is generally considered to rely on weak identification.

Similar as Dohmen et al. (forthcoming), we assume that the business cycle is one of the most important determinants of risk preferences, and we proxy the business cycle with gross domestic product (GDP) growth rates. The underlying idea is that individuals are more risk averse in economic busts and more risk loving in economic booms. Brandt and Wang (2003) have demonstrated that variations in aggregate risk aversion relate to business cycles: Risk aversion is high and/or rising in recessions and is low and/or falling during expansions (p. 1459). Bucciol and Miniaci (2013) have shown for Dutch panel data that risk preferences vary substantially with fluctuations in GDP. An important assumption is that the proxy is not linearly related to risk preferences, because in this case GDP growth rates would still not identify the period effect separately. Dohmen et al. (forthcoming) demonstrated for the same sample that the GDP growth rate is non-linearly related to risk attitudes. Finally, macroeconomic conditions may matter more for older birth cohorts or individuals from low socioeconomic backgrounds, therefore we test the hypothesis that these groups are more vulnerable to macroeconomic shocks. Finally, macroeconomic conditions may matter more for older birth cohorts or individuals from low socioeconomic backgrounds. We find evidence only that macroeconomic conditions affect birth cohorts differently, but not socioeconomic groups. Therefore, we include in our main specification interaction effects between birth cohorts and period effects.[10]

Despite the empirical evidence, it is still possible that GDP growth rates may not capture adequately the effect of the macroeconomic environment on risk preferences. Dohmen et al. (forthcoming) demonstrated that using alternative proxies for period effects - stock market indices, lagged GDP growth rate or yearly state unemployment rates - do not affect estimated age-risk tolerance profiles in the same data we use. Therefore, it does not matter which macroeconomic proxy researchers use. Moreover, it is possible that measures of risk aversion are context-specific, therefore a macroeconomic proxy of the outside environment maybe too noisy because other aspects of human life matter more in shaping risk perceptions. Although Dohmen et al. (2011) show that a global measure of risk attitudes strongly correlates with risk attitudes in various contexts (cor-

[10] We find evidence that macroeconomic conditions between 2004 and 2012 affect birth-cohorts differently, where older birth cohorts are more likely to benefit positively from positive macroeconomic conditions. The p-value of an F-test of equal coefficients across interaction effects between period effects and birth cohorts is 0.0048. In contrast, we find no evidence that macroeconomic conditions affect differently groups across the socioeconomic ladder. The p-value of an F-test of equal coefficients across interaction effects between period effects and e.g. education is 0.8849.

relation coefficients of over 0.5), risk attitudes in the context of financial matters predict more strongly the probability of holding stocks than general risk attitudes. Coppola (2014) suggests that survey-based, domain-specific measures of risk attitudes are more appropriate in predicting behaviors in each domain. In a robustness check we therefore use period fixed effects instead of GDP growth rates.

5 Estimation results

5.1 The age and socioeconomic gradient in risk preferences

First, we discuss the age- and socioeconomic-status-related determinants of risk tolerance obtained from both OLS and random effects regression models. These selected results are reported in Table 4 (Model 1). Statistical significance levels of 10%, 5%, and 1% are flagged with one, two and three stars, respectively. This first step explores the degree to which risk preferences co-vary with age and socioeconomic economic status before moving on to discuss the socioeconomic gradient in the lifecycle patterns of risk preferences (Section 5.2).

Risk tolerance and age are negatively and almost linearly related with each other. While adolescents under the age of 20 score almost one point higher on risk tolerance than individuals in the comparison group (36 to 41), individuals in the oldest age group (Age 76 or above) score one point lower. An F-test of equality of coefficients across all age groups is rejected (p-value < 0.01). The difference in risk tolerance between age group 41 to 45 and the comparison group is not statistically significant.

A socioeconomic gradient in risk preferences emerges across the education and income spectrum, but not across the occupation spectrum. Risk tolerance levels are highest for individuals with tertiary education and lowest for individuals with minimum levels of education. Individuals with minimum schooling or who completed an apprenticeship score 0.4 and 0.2 points, respectively, lower on risk tolerance than individuals with tertiary education (significant at the 1% level). A similar gradient emerges across the spectrum of disposable household income.

We find little evidence of differences in mean risk attitudes across occupational groups. Elementary workers tend to be less risk tolerant than the comparison group (professionals), but the magnitude of this difference is small (-0.14 points). The only large and significant difference is found between legislators and managers - who score almost half a standard deviation higher on risk tolerance - and professionals.

It could be the case that we do no detect strong differences in risk tolerance across occupations because the effects may differ substantially at the extreme ends of the risk tolerance distribution. We therefore also estimate two logit models in which we assess the effect of age and socioeconomic status on the probability to score high on risk tolerance (Model 2) and on the probability to score extremely low on risk tolerance (Model 3). The reported magnitudes refer to odds ratios, which are interpreted relative to the omitted category of the dummy variables, which takes the value of 1.

An occupational gradient emerges indeed at the left tail of the risk distribution as can be seen in Model (3). Individuals who work as operators, manual workers or skilled agricultural workers are roughly 2 times more likely to report extreme levels of risk aversion than individuals working as professionals. The same odds ratios are obtained for individuals who left the labor force or who are currently unemployed (relative to professionals). Yet, we cannot find the same occupational gradient at the higher end of the risk tolerance distribution.

5.2 Lifecycle patterns in the socioeconomic gradient of risk preferences

In this section we present the lifecycle patterns in risk tolerance by socioeconomic groups (Figure 1). We first discuss these lifecycle profiles without controlling for cohort effects to provide a big-picture overview of the gradients for all subcategories within each socioeconomic group and all age-data points available. All presented figures display the non-parametrically estimated bivariate relationship between the permanent component in risk tolerance - derived from an estimation model of risk tolerance that controls for the same control variables as in Model (1) in Table 4 - and age. Changes in risk tolerance over time are interpreted in terms of standard deviations.

Figure 1(a) demonstrates the lifecycle patterns across four income-quartile groups. There are no discernable differences in the dramatic drop of 0.5 SD in risk tolerance across income quartiles from age 20 to age 35. However, a socioeconomic gradient emerges from age 40 onward. While individuals in the richest income-quartile group increase their risk tolerance slightly up until retirement age by 0.2 SD, and the medium income-quartile groups stabilize their risk tolerance around the mean (score 0), individuals in the poorest income-quartile group continue to plummet almost linearly up until old age. Around retirement age, the gap in risk tolerance between the poorest and the richest is over 0.5 SD, which translates into a difference of over 1.15 units on the original score (0-10).

Almost identical lifecycle differences across socioeconomic groups emerge when using education or occupation measures to proxy socioeconomic status. No socioeconomic gradient exists before the age of 40, but around that age individuals with minimum schooling (Figure 1(b)) or working in non-skilled occupation/service jobs (Figure 1(c)) continue to drop in their risk-tolerance levels. The education gradient peaks in old age with a difference of almost 0.8 SD, which translates into a difference of almost 2 units on the original risk tolerance score. Less extreme is the occupational gradient in risk tolerance; while also peaking in old age, its maximum difference is 0.5 SD.

We also compare the lifecycle patterns in risk tolerance of individuals who were at least once in their life diagnosed with depression with healthy individuals (Figure 1(d)). Although individuals diagnosed with depression tend to report lower levels of risk tolerance at any age, the difference between healthy and not-so-healthy groups remains fairly stable over the lifecourse. We judge from Figure 1(d) that the growing socioeconomic gradient in risk tolerance over the life course is not the result of systematic differences in mental health across socioeconomic groups.[11]

5.3 Controlling for cohort effects

In this section we test whether the same lifecycle patterns in the socioeconomic gradient of risk tolerance are obtained when controlling for birth-cohort effects. This is important for two reasons. First, the very strong age gradient in risk tolerance reported in Figure 1 may be the result of differences in exposure to risk across cohorts. Older cohorts may have been exposed systematically more to risk than younger cohorts when born and/or throughout their puberty, and exposure to real risk may make individuals more

[11] We further compared the lifecycle patterns of risk tolerance for individuals diagnosed with high blood pressure and healthy individuals. At no point in time are individuals with high blood pressure more risk averse than healthy individuals, except for a very large gap at age 35-45. Provided upon request.

risk averse (e.g. Malmendier and Nagel, 2011). Alternatively, older cohorts may have been exposed to more risk-averse parenting styles than younger cohorts and thus became more risk averse themselves (e.g. Cameron et al., 2013). Second, it is likely that the emerging socioeconomic gradient in risk tolerance from age 40 onward is the result of a greater exposure to risk for disadvantaged families relative to better-to-do families in the older cohorts. For instance, individuals born into low socioeconomic background around World War II (Cohorts 1930-34, 1935-39, 1940-44, 1945-49) may have been more heavily exposed to food shortages and economic deprivation than people born into well-to-do families. In contrast, the younger cohorts (Cohorts 1965-69, 1970-74) were much less affected by socioeconomic disparities because of strong social equity and redistribution policies conducted by the social democrat government in the 1970s.

Figures 2 to 4 display the risk tolerance-age profiles (referred to as RT-age from here onward) for each of the twelve cohorts in the top and bottom of the socioeconomic ladder: minimum schooling versus university education; first versus fourth income quartiles; and manual/elementary versus professional/managerial occupations. Figures in the left panel graph the sum of RT-age profiles for each cohort followed over a nine-year window (non-parametric estimates). The RT-age profiles depicted in a long-dashed line refer to the low SES groups, while the ones depicted in a short-dashed line refer to the high SES groups. Except for the extreme ends of the age distribution, the RT profiles at each year of age overlap for three cohorts. It is these overlapping data that help us to approximate the true lifecycle profiles in RT.

Figures in the right panels graph the average difference in RT as individuals age between low and high socioeconomic groups (solid black line). For each age, the RT data used to construct this difference stems from an average that is taken across the number of cohorts for whom data are available at this age group. The light-grey lines depict the 95% confidence intervals. Standard errors used to construct the confidence intervals are obtained with the delta method.

Figure 2(a) compares the RT-age profiles between the richest and the poorest groups measured by household income quartiles. The profiles between the two groups are strictly overlapping up until age 45, but from then onward RT levels of each cohort in the poorer group fall dramatically, while RT levels remain constant, or increase, for the richest. It is important to note that the shapes of the RT-age profiles are highly non-linear for both income groups, but that they also differ substantially in old age. For the three oldest cohorts in the low-income group the RT-age profiles are strictly increasing or hump-shaped, while for the equivalent three richest cohorts they are U-shaped or mainly declining. Despite the shape differences for the older cohorts, the socioeconomic gradient in the RT-age profiles reaches a maximum of 0.4 SD at retirement age. Figure 2(b) displays the linear and significant increase in the socioeconomic gradient from age 45 until ages 65 and above.

An almost identical lifecycle pattern in RT emerges between groups of high and low levels of education (see Figures 3(a) and 3(b)). No discernable socioeconomic gradient in RT occurs until age 45, but a quick and steep decline in RT emerges for individuals with minimum schooling, while RT levels stabilize for individuals with university education. By age 65, the education gradient in RT reaches a maximum of 0.5 SD that remains constant into old age.

Although we find similar lifecycle differences in RT between skilled and unskilled occupational groups, the occupation gradient over the lifecourse that emerges from age 45 onward is only statistically significant at the 10% level and is less strong in magnitude (less than 0.2 SD) (Figures 4(a) and 4(b)). One reason is that occupational lifecycle gradients in risk tolerance are well captured by educational and income differences, for which we control in the estimation model. When dropping income and education variables in the estimation model, the differences in risk preferences between high and low levels of occupational skills is statistically significant at the 5% level between ages 45 and 65 (see Figure 1(b) in the Online Appendix).

We conduct two robustness checks to ensure that our findings are not driven by panel attrition or our proxy of environmental factors. First, emerging lifecycle patterns of risk tolerance across socioeconomic groups could be the result of a systematic dropout of highly risk-averse individuals from the top socioeconomic groups or of the highly risk-loving individuals from the bottom socioeconomic groups. However, when we drop individuals who are less than six out of the seven available time periods in the sample (21%) we obtain almost identical lifecycle patterns in the socioeconomic gradient in risk tolerance. The only difference is that the peak difference in risk tolerance between the bottom and the top socioeconomic groups is reduced by 0.1 SD (see Figures A.2, A.3 and A.4 in the Online Appendix).

Second, it is possible that we do not adequately capture environmental influences through our proxy of GDP growth rates. Therefore, we re-estimated the models using time fixed effect dummy variables instead. There is virtually no differences in the socioeconomic gradient in the lifecycle pattern of risk preferences (see Figures A.5, A.6 and A.7 in the Online Appendix).

6 Discussion and Conclusions

The major decisions of an individual's life regarding finances, health behaviors, and career choices are driven by perceptions of risk. Thus, understanding the dynamics of risk preferences and their heterogeneity over the lifecourse is of vital importance for policy-makers who seek to incentivize socially-desirable behaviors. We contribute to the current literature by exploring the heterogeneity in the lifecycle patterns of risk tolerance using data from a large nationally representative survey from Germany and controlling for birth-cohort effects. Similar to other studies, we also find a negative ageing effect in risk tolerance, but on average this effect is only present until mid-age. From mid-age onward, it is only the very disadvantaged groups that continue to dramatically decrease their risk tolerance. Using non-parametric techniques to estimate the age-risk profiles within each birth cohort, we also find that the relationship between age and risk tolerance is highly non-linear.

The magnitudes of the differences in risk tolerance across the education and income spectrum by retirement age are substantial. A 0.5 SD difference in risk tolerance between the bottom and the top groups translates into a 1.15 score difference on the original risk tolerance index (0-10). For instance, Dohmen et al. (2010) using the same risk-tolerance measure and data as we do, find that a 1 SD deviation increase in cognitive ability increases the response in risk tolerance by between 0.23 and 0.56 points on a 0 to 10 scale, depending on the control variables included (see Table 4 in Dohmen et al. (2010)). Translated into our context, a socioeconomic gradient in risk tolerance of 1.15 points before retirement age results in a difference in cognitive ability of at least two standard deviations. Dohmen et al. (2011), also using the same measure and data, show that a 1 SD increase in the willingness to take risks translates into a 6.1 p.p. higher probability to engage actively in sport, a 2.4 p.p. increase in the probability to be self-employed and a 2.9 p.p. increase in the probability to invest in stocks. Translated into our context in terms of percent increases, these numbers imply that the socioeconomic gap in risk tolerance before retirement is equivalent to a 5% difference in actively engaging in sport, a 14.3% difference in being self-employed, and a 4.3% difference in investing in stocks.

Our study has various strengths and limitations. The main strength is the use of a large, nationally-representative longitudinal survey that allows us to draw conclusions for a whole population. In addition, owing to the longitudinal nature of the data source, we have been able to model individual-specific random variations in the self reported risk attitudes explicitly. This is especially important as risk preferences could theoretically be influenced by random events that occur just before or during the interview (See Carney et al., 2010, for experimental evidence). Another advantage is that we have been able to control for birth-cohort effects when comparing the age-risk attitudes profiles between the groups of interest. Sample sizes are large enough within each birth cohort and age-group to obtain statistically meaningful results.

The main limitation of our study is that our measure of risk tolerance is not incentive compatible and cannot distinguish between the gain and loss domains. However, we have some certainty about the validity of our measure to act as a good proxy for experimentally-derived, incentive-compatible risk measures (Dohmen et al., 2011). Vieider et al. (2015) show for almost all of 30 countries considered that survey-based questions on general and financial risk attitudes capture well risk attitudes that are elicited from incentivized experiments.

The same survey-based measure of risk attitudes has been used successfully in Dohmen et al. (2010) to identify the link between risk attitudes and cognitive ability, in Dohmen et al. (2012) to demonstrate the strength of the intergenerational transmission of risk preferences, and in Dohmen et al. (forthcoming) to explore true ageing effects in risk preferences over the lifecourse. A similar self-reported measure has also been used to link macroeconomic conditions with financial risk preferences and behavior (Malmendier and Nagel, 2011; Sahm, 2013). Trading off incentive compatibility against larger sample sizes and longitudinal follow up seems to be a justifiable strategy to gain new insights about the lifecycle dynamics of economic preferences.

Finally, our result cannot be interpreted as a causal effect of socioeconomic status on the lifecycle dynamics in risk preferences. We are not able to say that increasing an individual's income or education causes higher levels of change in risk tolerance. All we can say is that we observe heterogeneity in the change of risk tolerance over time, and that socioeconomic status is a powerful distinction to capture this heterogeneity. Future research is needed to assess whether the socioeconomic gradient emerges due to a higher propensity to experience shocks or due to the experience of a faster decline in cognitive ability by individuals at the bottom of the socioeconomic ladder.

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Table 1: Risk Distribution of the estimation sample

	2004		2006		2008		2009		2010		2011		2012	
Risk	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
0	1,642	8.15	1,022	4.94	836	4.53	1,808	9.3	1,042	5.88	965	4.87	753	3.85
1	969	4.81	811	3.92	1,016	5.5	1,474	7.58	1,012	5.71	1,008	5.09	761	3.89
2	2,016	10	1,833	8.87	2,258	12.23	2,840	14.61	2,220	12.53	2,127	10.74	1,895	9.69
3	2,585	12.82	2,503	12.11	2,763	14.97	3,154	16.23	2,797	15.79	2,669	13.47	2,504	12.81
4	2,139	10.61	2,136	10.33	2,099	11.37	2,216	11.4	1,746	9.85	2,079	10.49	2,130	10.89
5	4,396	21.81	4,828	23.35	3,654	19.8	3,926	20.2	3,581	20.21	4,485	22.64	4,480	22.91
6	2,206	10.94	2,458	11.89	1,941	10.52	1,755	9.03	1,886	10.64	2,268	11.45	2,345	11.99
7	2,260	11.21	2,599	12.57	1,955	10.59	1,433	7.37	1,846	10.42	2,269	11.45	2,487	12.72
8	1,409	6.99	1,780	8.61	1,353	7.33	648	3.33	1,182	6.67	1,421	7.17	1,559	7.97
9	347	1.72	440	2.13	363	1.97	107	0.55	246	1.39	313	1.58	382	1.95
10	188	0.93	266	1.29	218	1.18	74	0.38	161	0.91	208	1.05	256	1.31
Total	20,157	100	20,676	100	18,456	100	19,435	100	17,719	100	19,812	100	19,552	100

Table 2: Summary statistics

	N	Mean	SD	Min	Max
Variable	Obs	Mean	Std. Dev.	Min	Max
Risk attitude	135807	4.423	2.309	0	10
Risk attitude > 7	135807	0.095	0.293	0	1
Risk attitude = 0	135807	0.059	0.236	0	1
Female	135807	0.524	0.499	0	1
Foreigner	135807	0.057	0.232	0	1
Married	135807	0.602	0.490	0	1
Age	135807	49.949	17.581	18	102
Age below 20	135807	0.026	0.159	0	1
Age 20 to 25	135807	0.079	0.270	0	1
Age 26 to 30	135807	0.062	0.242	0	1
Age 31 to 35	135807	0.067	0.250	0	1
Age 36 to 40	135807	0.083	0.276	0	1
Age 41 to 45	135807	0.099	0.299	0	1
Age 46 to 50	135807	0.100	0.301	0	1
Age 51 to 55	135807	0.094	0.292	0	1
Age 56 to 60	135807	0.085	0.279	0	1
Age 61 to 65	135807	0.079	0.269	0	1
Age 66 to 70	135807	0.083	0.275	0	1
Age 71 to 75	135807	0.067	0.249	0	1
Age 76 and above	135807	0.075	0.264	0	1
University degree	135807	0.214	0.410	0	1
Higher vocational degree	135807	0.189	0.392	0	1
Apprenticeship	135807	0.437	0.496	0	1
No qualification	135807	0.161	0.367	0	1
Household income	135807	24776.770	25115.790	0	3027805
Legislators	135807	0.102	0.303	0	1
Professional	135807	0.168	0.374	0	1
Technicians	135807	0.193	0.395	0	1
Clerks	135807	0.072	0.259	0	1
Service	135807	0.065	0.247	0	1
Skilled agricultural worker	135807	0.008	0.088	0	1
Craft	135807	0.109	0.312	0	1
Operator	135807	0.032	0.175	0	1
Elementary worker	135807	0.028	0.166	0	1
Work not listed	135807	0.019	0.135	0	1
Not working	135807	0.192	0.394	0	1
Unemployed	135807	0.011	0.105	0	1
Cancer	135807	0.046	0.210	0	1
Depression	135807	0.066	0.249	0	1
Stroke	135807	0.021	0.144	0	1
High blood pressure	135807	0.258	0.437	0	1
Dementia	135807	0.004	0.064	0	1
GDP growth rate(%)	135807	1.265	2.886	-5.1	4

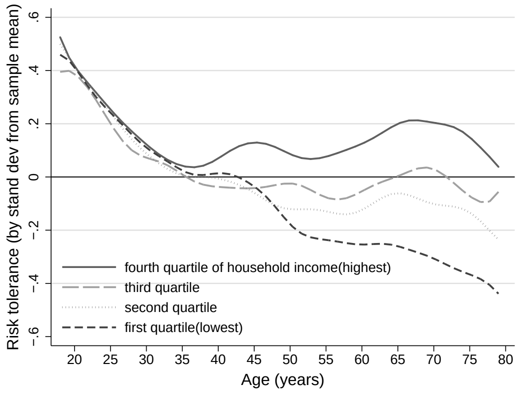
Table 3: Illustration of cohort averaged difference by age using four selected cohorts

	Age Spans																										
1940-4																60	61	62	63	64	65	66	67	68	69	70	71	72
1945-9											55	56	57	58	59	60	61	62	63	64	65	66	67					
1950-4						50	51	52	53	54	55	56	57	58	59	60	61	62										
1955-9	45	46	47	48	49	50	51	52	53	54	55	56	57															

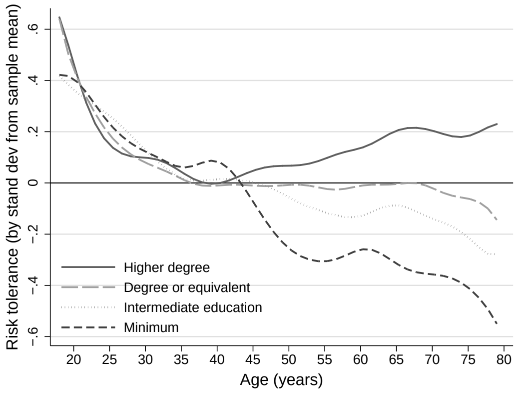
Table 4: Size effects of age and socioeconomic status on risk tolerance and the probability of high and zero risk tolerance[a]

	Model (1) Levels		**Model (2) High risk**		**Model (3) Zero risk**	
	OLS	FGLS-RE	Logit	Logit-RE	Logit	Logit-RE
Age groups - Base: Age 36-40						
Age below 20	1.11***	0.96***	2.17***	2.75***	0.41***	0.31***
Age 20 to 25	0.74***	0.67***	1.76***	2.21***	0.50***	0.42***
Age 26 to 30	0.36***	0.35***	1.32***	1.53***	0.69***	0.61***
Age 31 to 35	0.14***	0.13***	1.10**	1.19***	0.88	0.82*
Age 41 to 45	-0.01	-0.05*	0.99	0.91*	1.08	1.08
Age 46 to 50	-0.13***	-0.19***	0.91*	0.82***	1.45***	1.46***
Age 51 to 55	-0.22***	-0.26***	0.87**	0.78***	1.77***	1.91***
Age 56 to 60	-0.31***	-0.39***	0.79***	0.66***	1.81***	2.06***
Age 61 to 65	-0.32***	-0.47***	0.79***	0.61***	1.94***	2.43***
Age 66 to 70	-0.40***	-0.55***	0.72***	0.55***	2.12***	2.68***
Age 71 to 75	-0.52***	-0.65***	0.65***	0.46***	2.31***	2.98***
Age 76 and above	-0.88***	-0.92***	0.54***	0.36***	3.08***	4.18***
Education - Base: University						
Higher vocational degree	-0.14***	-0.13***	0.88***	0.84***	1.51***	1.77***
Apprenticeship	-0.22***	-0.20***	0.85***	0.80***	1.73***	2.17***
No qualification	-0.45***	-0.39***	0.79***	0.75***	2.40***	3.67***
Household income quartiles - Base: lowest						
Second	0.14***	0.08***	1.03	1.04	0.80***	0.83***
Third	0.18***	0.13***	1.07*	1.09*	0.66***	0.64***
Highest	0.37***	0.22***	1.31***	1.33***	0.54***	0.53***
Occupation - Base: Professional						
Legislators	0.49***	0.46***	1.57***	1.98***	0.83	0.77*
Technicians	0.03	0.01	1.01	1.01	1.12	1.16
Clerks	-0.02	-0.05	0.94	0.92	1.33**	1.41**
Service	0.05	0.04	1.07	1.15	1.37**	1.51***
Skilled agricultural worker	-0.11	-0.09	0.93	0.96	1.70**	2.14***
Craft	0.01	-0.06	0.99	0.96	1.30**	1.53***
Operator	-0.03	-0.09	1.02	1	1.57***	1.81***
Elementary worker	-0.06	-0.14*	1.11	1.13	1.74***	2.25***
Work not listed	0.13*	0.02	1.15*	1.23*	1.15	1.39*
Not working	-0.27***	-0.29***	0.84***	0.81***	1.81***	2.36***
Unemployed	0.20*	0.05	1.30**	1.23	1.89***	2.26***
Mean Risk[b]	4.423	4.423	0.204	0.204	0.059	0.059

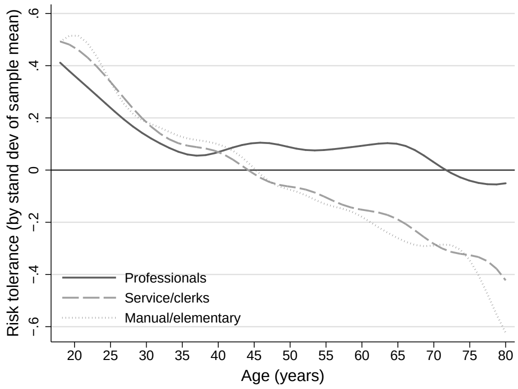
Total number of person-year observations is 135,807. All models control for gender, marital status, number of children in the household, being a foreigner, health conditions and the annual GDP growth rate (in %). [a] Columns 1-2 report coefficients from a linear regression model allowing for random effects. Columns 3-6 report odds ratios calculated from a random effects logit model. Odds ratio are statistically significant if different from 1. [b] Mean risk refers to sample proportions in columns 3-6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



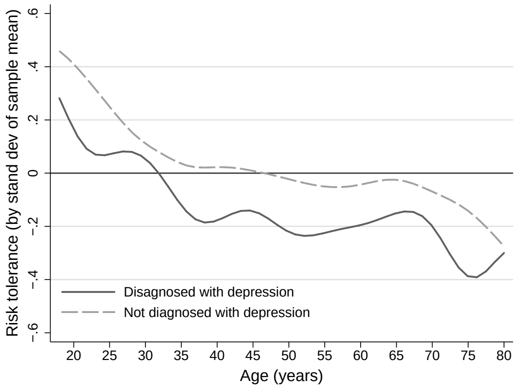
(a) Income



(b) Education

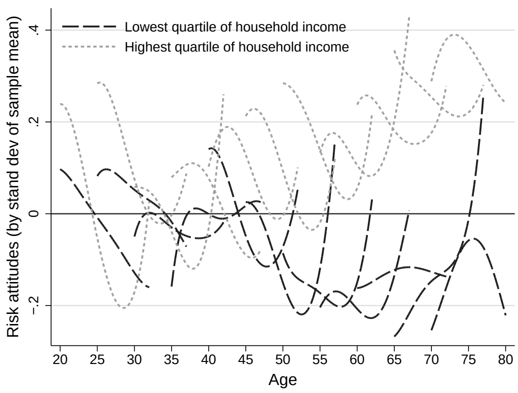


(c) Occupation

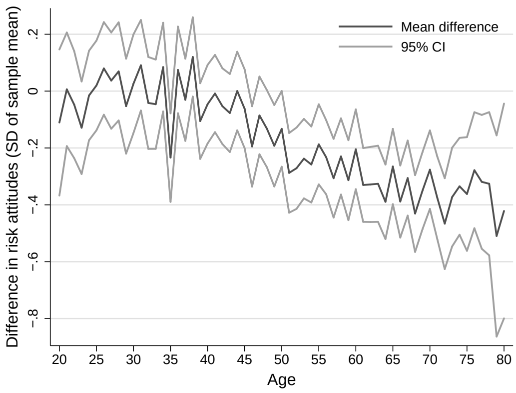


(d) Depression

Figure 1: Bivariate kernel estimates of the relationship between age and the adjusted permanent component of risk tolerance by socioeconomic status and mental health, no control for birth cohorts

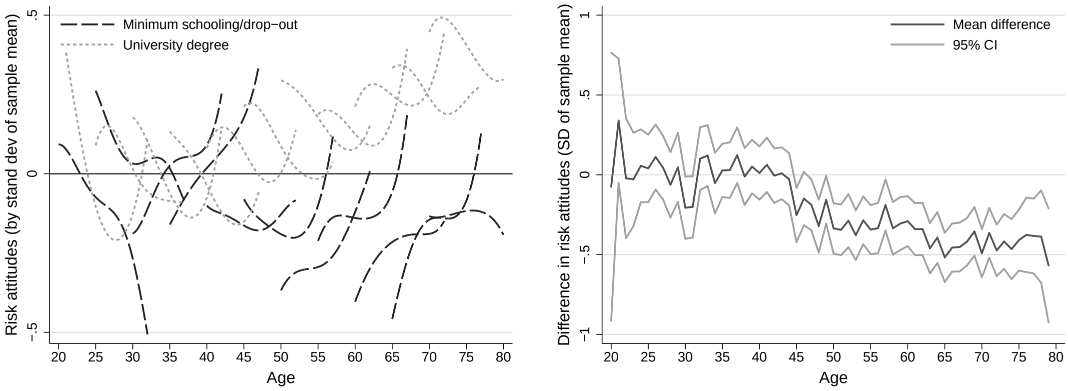


(a) Profiles



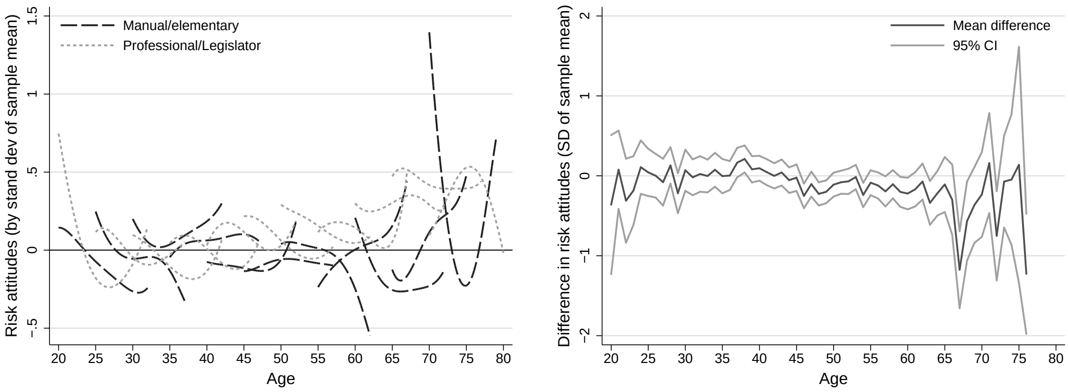
(b) Differences

Figure 2: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in the highest and lowest income quartile



(a) Profiles (b) Differences

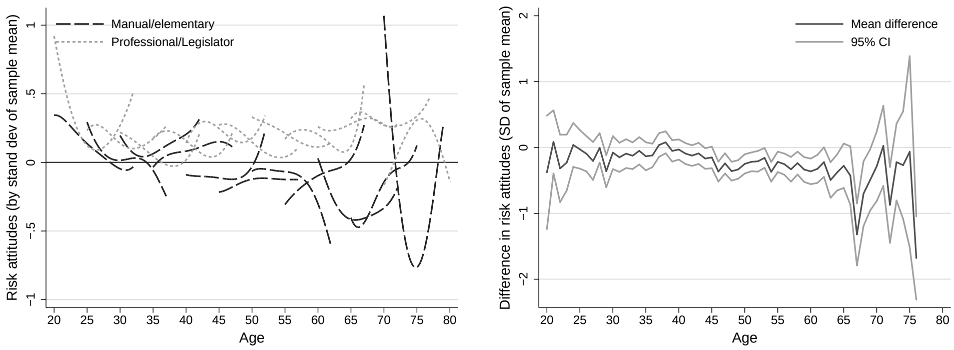
Figure 3: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals with tertiary and minimal education



(a) Profiles (b) Differences

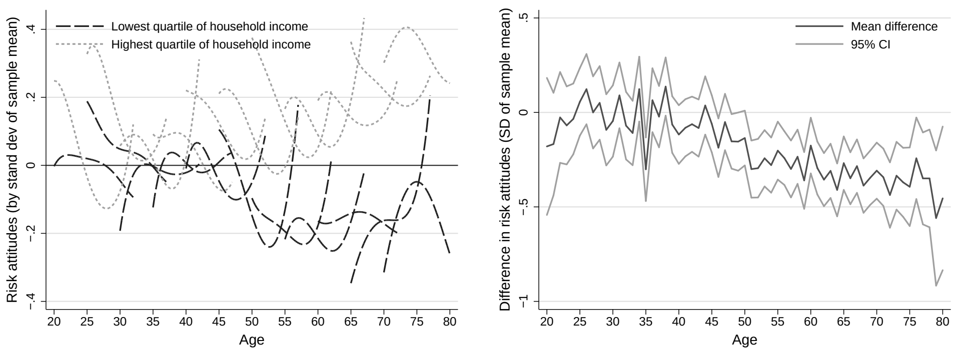
Figure 4: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in high- and low-skill occupations

A ONLINE APPENDIX - NOT FOR PUBLICATION*



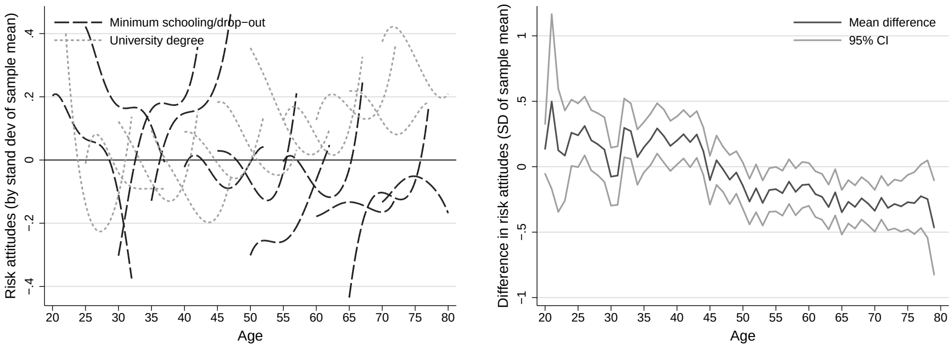
(a) Profiles (b) Differences

Figure A.1: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in the highest and lowest skill occupation, not controlling for education and income differences



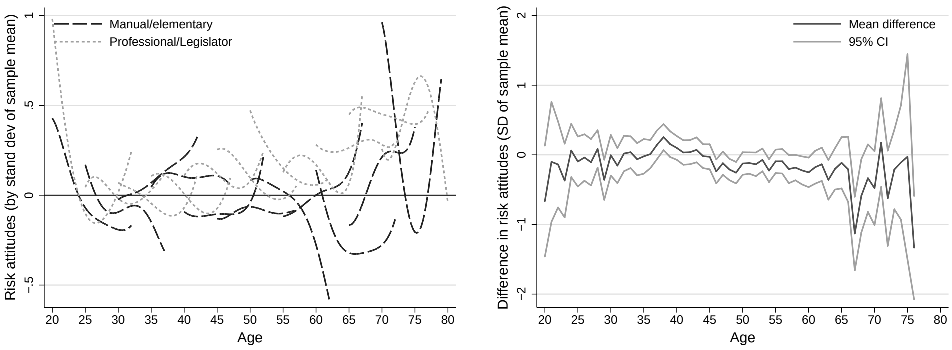
(a) Profiles (b) Differences

Figure A.2: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in the highest and lowest income quartile, removing individuals who have less than six years of data available



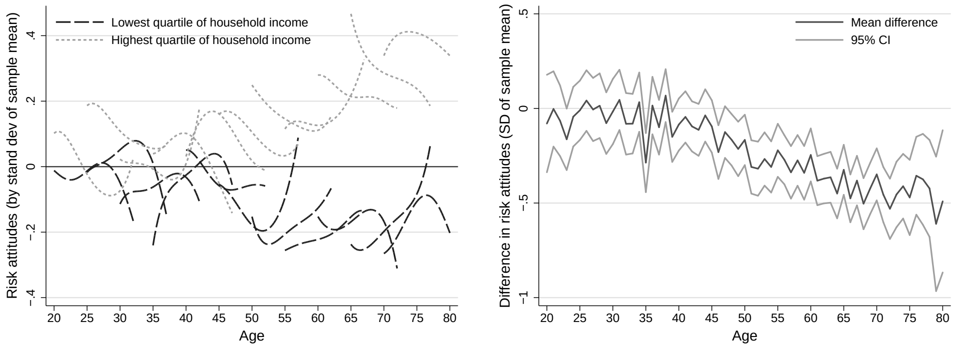
(a) Profiles (b) Differences

Figure A.3: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals with the highest and lowest education levels removing individuals who have less than six years of data available



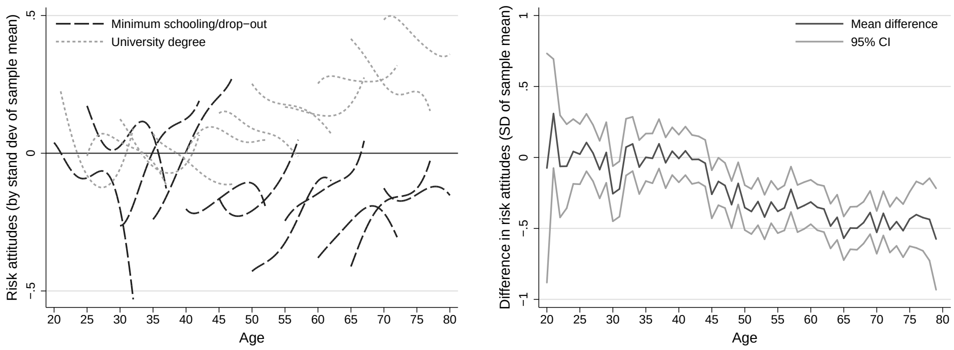
(a) Profiles (b) Differences

Figure A.4: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in the highest and lowest skill occupation, removing individuals who have less than six years of data available



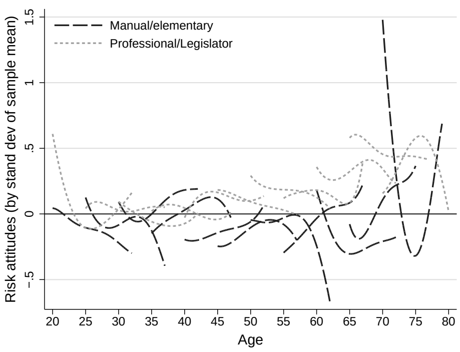
(a) Profiles (b) Differences

Figure A.5: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in the highest and lowest income quartile, using time fixed effect dummy variables to control for period effects

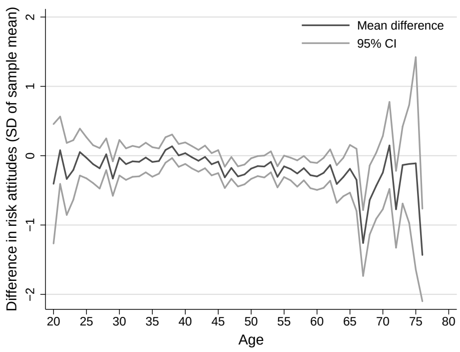


(a) Profiles (b) Differences

Figure A.6: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals with the highest and lowest education levels, using time fixed effect dummy variables to control for period effects



(a) Profiles



(b) Differences

Figure A.7: Bivariate kernel estimates of the relationship between age and the adjusted, permanent component of risk tolerance within birth cohorts, separately for individuals in the highest and lowest skill occupation, using time fixed effect dummy variables to control for period effects

Table A.1: Summary of Literature Review

Paper	Data	Sample Size	Methodology	Findings	Contributions/ Drawbacks
Tymula et al. (2013)	1) Lottery experiments including 320 choices(160 gain, 160 loss) with certain(risky) or unknown(ambiguous) probabilities; 2) A demographic, financial and psychological profile(gender,education, household wealth, numeracy, IQ)	135 healthy subjects, including 33 adolescents(age 12-17), 34 young adults(21-25), 32 midlife adults(30-50), and 36 older adults(65-90)	1) Model free analysis; 2) Model based analysis: first build a model including individual risk and ambiguity attitudes, and stochasticity, then use maximum likelihood method to estimate the parameters	1)Older adults generate lowest income in the experiments; 2) Older adults choose dominated choices most often;3)Older adults are more inconsistent(not random) in their choices;4)In the gain domain, adolescents and older adults are more risk averse, and adolescents are more ambiguity tolerant, i.e. risk attitudes show an inverted U-shape with age in the gain domain. In the loss domain, older adults are more risk seeking and ambiguity averse;5)The results are robust controlling for socioeconomic and demographical variables, and to model free analysis, and differences in risk and ambiguity attitudes were not caused by some systematic differences between the groups in total wealth, education, IQ, or numeracy scores.	1)Sample size too small;2)Participants only have 10s for each trial;3)Use parents' education level as adolescents' education level;4) Use household wealth as adolescents' wealth;5)Exceptionally high proportion of midlife adults and older adults have advanced graduate degrees, so the sample may not be representative;

Table A.1: Summary of Literature Review

Paper	Data	Sample Size	Methodology	Findings	Contributions/ Drawbacks
Dohmen et al. (2011)	1) The 2004 wave of German Socio-Economic Panel(SOEP), including detailed personal and household information, and a general risk question; 2) A field experiment (using the exactly same sampling methodology with SOEP(targeted random walk method), but a different subject pool to avoid participants from SOEP) including a questionnaire as in SOEP and a lottery experiment	1)22,019 individuals over age 17 in 11,803 different households; 2) 450 subjects	1) Interval regression; 2) Principle components analysis; 3) Probit model	1)Being male, height, parental education level, household income, life satisfaction are significantly positively correlated with risk attitudes, while age, being widowed, bad subjective health status, being out of the labor force and number of children are significantly negatively correlated with risk attitudes; 2)Answers to the general risk question can well predict actual risk-taking behaviour, even controlling for a wide range observable characteristics; 3) Effects of gender, age, height, and to some extent, parental education, on risk attitudes are similar and significant across contexts, after adding additional controls;4) Risk attitudes are highly and significantly correlated across contexts, and around 60% of individual risk attitudes s explained by one principle component, indicating a stable common underlying risk trait;5) The general risk question is the best all-round predictor of risk attitudes, but the risk question in specific context is a stronger measure in that context;	This study validated the often used survey data as a good measure of real risk preferences, and indicated that experiments with lottery questions, which is also very often used in the area, may not be very effective in indicating risk preferences in non-financial contexts; The coefficient of answers to the general question on value of safe option at switching point if statistically, but not economically significant.
Dohmen et al. (2010)	Cognitive ability, risk attitudes and personal profiles from a representative sample	452 participants (age 17 and older)	Interval regression method	Higher cognitive ability is associated with greater willingness to take risks, controlling for individual characteristics such as gender, age, and height, as well as important economic variables including education, income, and liquidity constraints.	Cognitive ability are mainly related to processing speed, and may not be representative

Table A.1: Summary of Literature Review

Paper	Data	Sample Size	Methodology	Findings	Contributions/ Drawbacks
Dohmen et al. (forthcoming)	1) The Dutch DNB household survey(DHS) from 1993-2001, 6 financial risk questions were included each year; 2) 2004, 2006, 2008-2011 waves of the German Socio-Economic Panel (SOEP);	1) 35,173 observations (aged 16 onwards) in total for DNS; 2) 120,954 observations (aged 17 onwards) for SOEP	1) The two data sets were analysed in parallel; 2) GDP growth rate used as proxy for calendar time effect, as GDP growth is not linearly correlated with time periods, but is positively correlated with average attitudes;	1) By pooling all years together and plotting average risk attitudes on age, the authors found a negative linear age effect on risk attitudes, and that men are more risk taking than women;2) Age coefficients of regressing risk attitudes on age, controlling for cohort effect and calendar time effect, are significantly negative and of similar size for both data sets; 3) After controlling for cohort effect and calendar time effect, the slope of the age pattern of risk attitudes are approximately linear, which becomes flatter after age 65; 4) After controlling for cohort effect and calendar time effect, difference of risk attitudes between men and women rises sharply until age 25, and stays positive and stable after that; 5) Age effects are significantly negative using fixed effect model and controlling for calendar time effect	The non-response rate for young people is rather high in the Dutch data set, with 40% of women younger than age 30 have non-missing observations on all six questions, and the response rate for men increases linearly from 40% at age 30 to about 70% at age 80;
Donkers et al. (2001)	First wave of Dutch CentER Savings Survey (CSS) drawn in 1993, including 8 risk questions and detailed background information	3949 individuals aged 16 and above	Semiparametric estimation and structural model based on Cumulative Prospect Theory	Age and being female have negative effects on risk attitudes, while income and education level are positively correlated with risk attitudes	Survey questions are answered online by the respondents themselves instead of by personal interviews, so respondents may answer with less care;
Baltes and Lindenberger (1997)	Composite sample combining younger adult sample and a subsample of BASE (age 25-101);	315(171(age 25-69), 144(age 70-101));	Visual acuity, auditory acuity and 5 cognitive abilities are measured, and then linear regression is used for analysis;	1) Vision, hearing and cognitive abilities all show clear negative age effects; 2) The negative age effects on cognitive abilities are extremely well predicted by individual differences in vision and hearing;	Cohort effects are not controlled;
Frederick (2005)	CRT and risk preferences data obtained from mostly undergraduate students with a questionnaire including CRT and several lottery questions	3,428 respondents	A three-item "Cognitive Reflection Test" (CRT) is used as a simple measure of one type of cognitive ability	1) In the domain of gains, the high CRT group are more willing to gamble, even when the gamble has lower expected value. This suggests that correlation between cognitive ability and risk preferences in gains is not only due to higher computation skill; 2) In the domain of losses, the high CRT group is less risk seeking; 3) Males score significantly higher in CRT than females; 4) Females are significantly more risk averse than males, controlling for CRT scores;	Participants are mostly university students with many similar characteristics, so more variance should be observed using representative sample

Table A.1: Summary of Literature Review

Paper	Data	Sample Size	Methodology	Findings	Contributions/ Drawbacks
Burks et al. (2009)	Cognitive skills, risk attitudes (lottery experiment), and personal profiles from a sample of trainee tractor-trailer drivers at a big U.S. trucking company	1,066 individuals	Constant relative risk aversion utility function used to measure risk aversion	1) People with higher cognitive skills(CS) are more willing to take calculated risks in the domain of gains; 2) People with higher CS are less risk taking in the domain of losses; 3) Individuals making choices close to risk neutrality have significantly higher CS than those making choices farther from risk neutrality	Sample may not be representative
Benjamin et al. (2013)	Paid lottery experiments and demographic information from students in a Chilean high school	92 senior students	Cognitive ability is measured by standard math score; Ordered probit model	The effect of math score on risk attitudes is positive, and marginally statistically and economically significant, controlling for gender and average income of the neibourhood	Sample not representative; Preference measure may not be general
Bonsang and Dohmen (2012)	Survey of Health, Ageing and Retirement in Europe (SHARE) that includes both a question on financial risk preference and measures of cognitive ability(episodic memory, verbal fluency and numeracy) for a representative sample of individuals aged 50+ in 11 European countries	11,662 observations	1) 2)Correcting for attenuation bias that results from measurement error in the cognitive skills measure by using the lag of the measured cognitive score as an instrument for the noisy contemporaneous cognitive skills measure	1) Older cohorts are less willing to take financial risks than younger cohorts;2)Cognitive abilities decline with age;3)By comparing age effects on risk attitudes in a regression framework with and without controlling for cognitive abilities, the authors found that about two fifth of the age-related cross-sectional difference in risk attitudes can be explained by cognitive abilities; After correcting for attenuation bias, the age effect is reduced by about 70%, and is captured by cognitive abilities. These findings suggest that the difference in willingness to take risks between cohorts can be traced to age related differences in cognitive functioning.	Answers to financial risk question may not be representative of a person's general risk attitude

Table A.1: Summary of Literature Review

Paper	Data	Sample Size	Methodology	Findings	Contributions/ Drawbacks
Carney et al. (2010)	Field experiment where participants were randomly assigned to do high or low power poses, then different indicators of power were measured	Forty-two participants (26 females and 16 males)	Risk preferences, feelings of power, and hormone levels were compared to determine whether the power-pose could make people more powerful	high-power poses caused an increase in testosterone compared with low-power poses, which caused a decrease in testosterone; high-power poses caused a decrease in cortisol compared with low-power poses, which caused an increase in cortisol; high-power posers were more likely than low-power posers to be risk seeking; high-power posers reported feeling significantly more "powerful" and "in charge"	Sample size too small;

Table A.2: Number of Observations with Retrospective Occupations

	Without	With	Difference
Work not listed	3455	2530	941
Not working	37899	26115	11839
Unemployed	2611	1505	1186
Total	43965	30150	13815

1) There are 43965 observations without occupation information using 2004-2012 waves, and they are allocated into the above three categories according to their labor force status. Then we use all waves from 1984 and try to capture more occupation information from the earlier waves. After this, only 30150 observations are without occupation information, i.e. 13815 observations are with retrospective occupations.

2) For the observations with age above 30 in "not working", 63.82% are female, which are likely to be housewives.

Table A.3: Occupation Reassignment

	Freq.	Percent	Cum.
0	30,150	22.2	22.2
1	54,474	40.11	62.31
2	32,382	23.84	86.16
3	13,468	9.92	96.07
4	4,249	3.13	99.2
5	902	0.66	99.87
6	168	0.12	99.99
7	14	0.01	100
Total	135,807	100	

Table A.3 shows the number of occupations that individuals have had. For individuals who have had more than one occupations, we assign the highest one as their life-long occupation in the order "legislators > professionals > technicians > clerks > craft > service > operators >skilled agriculturist > elementary". Among the 51183 observations that have been reassigned occupations, 8566 are considered as high jumpers (legislators or professionals who have had occupations in service, elementary or craft).

Table A.4: Number of observations in each age cohort in the cohort analysis

All	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	2549	1719	1442	1797	2075	2178	2073	1576	1337	2056
2006	2578	1787	1495	1835	2018	2183	2086	1615	1326	2267
2008	2213	1591	1322	1592	1778	1919	1832	1414	1171	1938
2009	2263	1696	1406	1732	1873	1990	1940	1459	1212	1963
2010	2028	1573	1323	1592	1730	1799	1722	1322	1095	1722
2011	2285	1735	1514	1792	1943	2016	1883	1451	1189	1893
2012	2191	1718	1517	1754	1924	1968	1876	1422	1189	1822
Total	16,107	11,819	10,019	12,094	13,341	14,053	13,412	10,259	8,519	13,661

Cohorts 35-39 and 80-84 are of 9 and 8 year intervals respectively, while other cohorts are of 5 year interval.

Table A.5: Number of observations in each age cohort in the cohort analysis by gender

Female	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	1,278	866	700	935	1,081	1,114	1,062	834	720	1,038
2006	1,299	903	727	972	1,067	1,142	1,070	860	729	1,174
2008	1,139	797	654	843	951	990	945	754	636	1,022
2009	1,171	856	696	915	1,003	1,021	1,006	778	661	1,029
2010	1,045	787	663	850	927	931	893	701	607	913
2011	1,164	881	767	963	1,032	1,047	1,000	781	667	1,032
2012	1,118	882	762	953	1,032	1,042	1,009	765	673	973
Total	8,214	5,972	4,969	6,431	7,093	7,287	6,985	5,473	4,693	7,181
Male	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	1,271	853	742	862	994	1,064	1,011	742	617	1,018
2006	1,279	884	768	863	951	1,041	1,016	755	597	1,093
2008	1,074	794	668	749	827	929	887	660	535	916
2009	1,092	840	710	817	870	969	934	681	551	934
2010	983	786	660	742	803	868	829	621	488	809
2011	1,121	854	747	829	911	969	883	670	522	861
2012	1,073	836	755	801	892	926	867	657	516	849
Total	7,893	5,847	5,050	5,663	6,248	6,766	6,427	4,786	3,826	6,480

Cohorts 35-39 and 80-84 are of 9 and 8 year intervals respectively, while other cohorts are of 5 year interval.

Table A.6: Number of observations in each age cohort in the cohort analysis by education

No qualification	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	627	272	226	241	223	245	244	218	169	660
2006	611	285	210	239	207	242	229	196	161	561
2008	491	233	180	186	175	204	189	167	145	326
2009	500	236	194	187	175	198	194	167	152	295
2010	435	209	177	162	157	168	164	141	119	247
2011	547	247	220	211	191	218	197	179	145	278
2012	497	242	209	197	177	212	192	169	149	254
Total	3,708	1,724	1,416	1,423	1,305	1,487	1,409	1,237	1,040	2,621
University Degree	**35-39**	**40-44**	**45-49**	**50-54**	**55-59**	**60-64**	**65-69**	**70-74**	**75-79**	**80-84**
2004	470	425	372	502	583	509	456	315	165	23
2006	490	430	371	518	574	520	469	368	250	73
2008	439	403	336	453	505	466	419	339	272	171
2009	432	416	352	481	532	485	451	363	319	250
2010	405	406	333	457	495	442	408	339	307	300
2011	425	440	352	492	509	494	451	337	322	395
2012	419	452	359	477	502	476	447	345	324	466
Total	3,080	2,972	2,475	3,380	3,700	3,392	3,101	2,406	1,959	1,678

Cohorts 35-39 and 80-84 are of 9 and 8 year intervals respectively, while other cohorts are of 5 year interval.

Table A.7: Number of observations in each age cohort in the cohort analysis by income

Lowest income	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	952	489	248	277	357	450	515	447	468	620
2006	970	573	294	318	341	428	484	429	442	807
2008	808	452	283	271	268	298	356	312	322	659
2009	852	509	324	302	272	307	342	298	314	662
2010	728	445	313	286	255	258	292	255	245	564
2011	819	508	349	323	302	279	311	283	266	604
2012	710	477	358	357	284	259	302	247	276	564
Total	5,839	3,453	2,169	2,134	2,079	2,279	2,602	2,271	2,333	4,480
Highest income	**35-39**	**40-44**	**45-49**	**50-54**	**55-59**	**60-64**	**65-69**	**70-74**	**75-79**	**80-84**
2004	345	443	567	639	601	483	386	239	197	416
2006	366	416	553	681	665	541	431	282	198	392
2008	344	393	464	620	637	543	437	296	186	365
2009	313	395	464	680	708	602	508	315	232	374
2010	303	386	437	632	674	604	455	314	220	346
2011	348	410	474	656	769	710	545	340	251	375
2012	324	391	438	639	746	724	572	358	282	387
Total	2,343	2,834	3,397	4,547	4,800	4,207	3,334	2,144	1,566	2,655

Cohorts 35-39 and 80-84 are of 9 and 8 year intervals respectively, while other cohorts are of 5 year interval.

Table A.8: Number of observations in each age cohort in the cohort analysis by occupation

Low occupation	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	240	163	141	150	170	153	135	79	49	73
2006	210	149	143	150	162	162	142	77	53	93
2008	181	137	122	126	140	138	129	70	42	76
2009	168	126	126	150	152	153	145	80	54	90
2010	141	118	116	132	142	132	124	71	44	74
2011	118	106	119	148	182	162	137	86	60	95
2012	100	96	109	139	179	169	141	92	68	97
Total	1,158	895	876	995	1,127	1,069	953	555	370	598
High occupation	35-39	40-44	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84
2004	549	770	791	1,043	1,259	1,298	1,213	937	781	883
2006	527	729	782	1,053	1,214	1,305	1,230	960	778	1,001
2008	473	672	706	933	1,076	1,175	1,096	865	714	949
2009	444	655	683	983	1,115	1,186	1,127	876	733	974
2010	404	620	654	917	1,029	1,072	1,012	796	668	873
2011	363	590	647	967	1,092	1,168	1,067	843	694	949
2012	313	542	608	918	1,056	1,108	1,047	804	673	905
Total	3,073	4,578	4,871	6,814	7,841	8,312	7,792	6,081	5,041	6,534

Cohorts 35-39 and 80-84 are of 9 and 8 year intervals respectively, while other cohorts are of 5 year interval.